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# Relationship between leaf area index of wheat crop and different spectral indices in Punjab

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## ABSTRACT

This study was carried out to estimate the suitability of IRSP6LISS-III data for estimating LAI in wheat crop in Punjab conditions. LAI of 45 placescovering three agro-climatic regions of Punjab were surveyed where two-thirds of the data (30 cases) were allocated by random sampling to the modeling set and one-third (15 cases) to the validation set. The empirical relationships between wheat-LAI and satellite acquired spectral reflectance data were studied using correlation analysis, linear and non-linear regression analyses. Useful spectral features included single band reflectance inIR, logarithmic transformation of IR band reflectance and several spectral vegetation indices like RDVI, DVI, NDVI, SR, MSAVI2 and MSI. Amongst the LISS III bands, relationship between IR reflectance and the LAIwas the strongest (in polynomial function, r = 0.86; RMSE = 0.31i.e. 7.4 % of observed mean). However, LAI could be predicted most accurately by RDVIusing linear function ($R^2$(r)= 0.78 (0.88); RMSE, 0.27 i.e. 6.3% of observed mean). Keeping in view the high accuracy of estimates, 24 regression models developed through this study can be employed for wheat LAI estimation in the Punjab region of India.

***Key words:*** Wheat, LAI, Spectral reflectance, Vegetation-Indices, Satellite, Punjab

Leaf area index (LAI) is an important biophysical variable in many ecological and environmental applications such as in the regional ecosystem models (Waring and Running, 1998). LAI controls many biological and physical processes in the water, nutrient and carbon cycle (Waring and Running, 1998) and hence determines the biomass gain by the crop.

The possibility of estimating LAI by satellite remote sensing has been investigated in several studies at various spatial scales and environments (Stenberg *et al.,* 2004). In general, the estimation of LAI is based on empirical relationships establishedbetween the variable (LAI) measured in the field and satellite data of band reflectance, often expressed in the form of spectral vegetation indices (SVIs) (Table 1). In general, SVIs attempt to enhance the spectral contribution of vegetation while minimizing that of the background. SVIs using some combination of red and near-infrared (NIR) reflectances, like the simple ratio (SR) or the normalized ratio (Normalized difference vegetation Index, NDVI) have been particularly popular. However, the empirical relationships are affected by various factors including lodging, weed population and soil background reflectances. A set of soil-adjusted vegetation indices like SAVI and GESAVI have been developed to reduce the effects of the soil background reflectance (Major *et al.*, 1990, Qi *et al.*, 1994 and Rondeaux*et al.*, 1996).

If we wish to use satellite data to map LAI of wheat crop, it is necessary to understand how this variable relates to the satellite observed reflectance. The aim of this study was to examine the potential of the satellite data for estimating LAI of wheat in Punjab state, India. The statistical relationships between the field measured LAI and satellite data were studied using correlation analysis and models developed by linear and non-linear regression analyses. The studied spectralfeatures included the single band reflectance, its log transformation and several spectral vegetation indices (SVIs).

## MATERIALS AND METHODS

### *Study area*

The study area consists of whole of Punjab state of India. The area lies in the north–west part of India and is characterized by semi-arid climate with extreme winters. The mean temperature of the coldest month (January) is 13°C and that for the warmest month (June) is 34°C. The mean annual precipitation of the state is 648.8 mm, more than 75 percent of which is received during the three monsoon months (July-September). Most of the state lies in the Trans-Gangetic plain zone with an average elevation of approximately 300 m above the mean sea level andthe predominant soil type of Punjab is alluvial sandy loam.

### *Field data*

The field survey for LAI was conducted during the month of February in two successive years, 2007 and 2008. This time of field sampling coincides with good canopy coverage of wheat crop for almost all parts of the state. The data were collected from 45 sites covering three different agro-ecological regions of Punjab. The locations of the sites weredeterminedusing a handheld GPS device (Magellan Meridian Platinum). According to the manufacturer, the device has an accuracy of 7m or better for 95% of the time. Furthermore, the GPS measurements were averaged over several minutes in order to obtain measurements with enhanced accuracy.

### *Remotely sensed data*

IRS-P6 LISS III data for the years 2007 and 2008 were used.For the purpose of this research, NDVI was regarded as potential LAI for each pixel.

### *Image processing*

The 8 bit satellite imageries coinciding with the period of field sampling wereexported into the PCI_Geometica software and the NDVI of each pixel (DN-value ranges between 0 and 255) scaled between -1.0 to + 1.0.The output NDVI images of both the dateswere integrated to generate a single LAI zone using the threshold criteria given by NRSC (National Remote Sensing Centre) (NDVI <0.06, Non Agriculture; 0.06 - 0.10, Poor; 0.10 - 0.20, Moderate; 0.20 - 0.40, Good; >0.40, Excellent).

### *Data analysis*

Two-thirds of the data (30 cases) were allocated by random sampling to the modelling set and one-third (15 cases) to the validation set. Linear and non-linear models were developed between the LAI and spectral features using correlation analysis, linear and non-linear regression analysis. The estimation errors were studied throughthe validation set. The reduced major axis (RMA) regression instead of ordinary least squares (OLS) was used in this study as recommended by Curran and Hay (1986) and Cohen *et al.*, (2003). According to the above authors,the ordinary least squares (OLS) regression is often an inappropriate method for relating remotely sensed data to ground variables. OLS assumes that it is possible to specify 'independent' and 'dependent' variables, and that the independent variable is measured without error. It is difficult to make the specification and fulfill the assumptions in the case of remotely sensed data (Curran and Hay, 1986). Furthermore, the predictions by the OLS tend to have attenuated variation in the direction of estimation compared to the observed values (Cohen *et al.*, 2003). The terms of the linear model (y=ax + b) were calculated as follows

$$a = \frac{\sigma y}{\sigma x} \quad b = \overline{y} - \overline{ax}$$

Where, $\overline{y}$ and $\overline{x}$ are the means of the variables 'y' and 'x' respectively and $s_y$ and $s_x$ the corresponding standard deviations. The sign of the slope term 'a' was determined from the correlation analysis. The crop variable (LAI) was 'y' and spectral features are represented by 'x' in the present study.

Several studies (e.g. Myneni*et al.*, 1997) have reported non-linear relationships between the forest variables and reflectance data. Therefore, also the log transformations of band reflectanceand the applicability of exponential ($y=ae^{bx}$) and polynomial ($y= ax^2+bx+c$) models were examined. The models were linearised and parameters 'a' and 'b' estimated using RMA regression. The best type of model in terms of coefficient of determination ($R^2$) was chosen for each feature. The reliability statistics included the root mean square error (RMSE), relative RMSE (RMSEr), bias (Bias) and relative bias (Biasr) (Hyvonen, 2002):

$$RMSE = \sqrt{[\{ {}^{n}\Sigma_{i=1} (\hat{y}_i - y_i)^2\} / n]}$$

$$RMSE_r = (RMSE / \overline{y}) * 100$$

$$Bias = [\{ {}^{n}\Sigma_{i=1} (\hat{y}_i - y_i)\} / n]$$

$$Bias\ r = (Bias / \overline{y}) * 100$$

Where, $\hat{y}_i$ is the estimated value from model, $y_i$ is the observed value, $\bar{y}$ is the mean of observations and n is the number of observations. The statistical significance of the bias was estimated by the t-test (Ranta*et al.,* 1998)

$$t = \text{Bias} / (S_D/\sqrt{n})$$

where, SD is the standard deviation of the residuals ($\hat{y}_i$ - $y_i$). The bias was considered to be significant if the absolute value of the t was greater than t corresponding to the probability of 0.05 (Hyvonen, 2002)

## RESULTS AND DISCUSSION

### *Models for LAI*

Linear, polynomial and non-linear (exponential) regression models for estimating wheat LAI with spectral features as predictors (independent variable) were developed. Among these,eight (8) spectral features could be identified as most reliable (Table 2). The error statisticsthat includedrelative bias, relative RMSE and coefficient ofdetermination ($R^2$) ofthese models are presented in Table 3.In case of linear models,$R^2$ varied between 0.41 and 0.78 whereas for exponential and polynomial models the same ranged between 0.42 to 0.78 and 0.49 to 0.79 respectively. All the spectral bands were significantly correlated ($p \leq 0.05$) with LAI.Infra-red band (IR) reflectance showed strongest correlation with LAI (r = 0.80). Linear correlations with IR and G band reflectance were positive whereas correlations were negative with that of R and SWIR. The standard logarithmic transformation of IR band reflectance was found to enhance the correlation with LAI (r=0.83).

The lowest RMSE was 0.26(6.1 % of observed mean) for LAI predicted by DVI through polynomial function. The next best predictors in terms of RMSE were RDVI, NDVI,SR and MSAVI2 wherein RMSEs varied between 0.27 (6.3 %) and 0.33 (7.8%). The highest correlations between estimated and observed LAIs were obtained when RDVI and DVI (r = 0.89) had been used.LAI prediction with the developed models (Table 2) using the eight spectral features resulted in slight underestimation(negative bias) except in two cases. However, the biases were not statistically significant for any of the linear models.

In case of exponential models, RDVI had the smallest RMSE, 0.28(6.6 %) and strongest correlation (r = 0.88) between estimated and observed LAI.This RMSE was slightly higher, correlation weaker and relative bias, largerthan that in the correspondinglinear models.The biases in all the exponential model estimates were negative and comparable to their linear counterpart. However, models with band R, G and SWIR and their standard logarithmic transformations(not presented in the table) had the highest negative biases which were also significant($p \leq 0.05$).

In case of polynomial models,DVI had the smallest RMSE,0.26 (6.1%) and strongest correlation (r = 0.89) between estimated and observed values and also its RMSE was slightly smaller and correlation stronger than those of the best linear and non-linear exponential models.

### *Model evaluation*

In case of linear models with band R, SWIR and log Greflectance, $R^2$ values were quite low and it did not improve significantly when non-linear models were tried, hence not prescribed. The chlorophyll pigment in the green leaves absorbs radiation in red (R) wavelength but reflects strongly in the near IR region (Tucker and Sellers 1986). This fact might have contributed to the strongest correlation of near IR, among other LISS III bands, with LAI. The best models explained around 78 % of the variation in the LAI values. The lowest RMSE was 0.26(6.10%).Overall, the relative RMSEs in these model predictions were comparable to similar other studies.

All models were scored based on the error statistics and ranked accordingly. A model was considered more reliable when values for relative RMSE and biases were lower and $R^2$ higher. Of the all eight spectral features, overall, the use of RDVI was judged best followed respectively by DVI, NDVI, SR, MSAVI2, Log IR, IR and MSI.However, except Log IR, IR and MSI,the relative differences in theestimationpower of LAI by the other spectral features were very small.In a previous study, White *et al.,* (1997) reported SR and NDVI as the best indices to estimate LAI for low and medium values. Whereas, SAVI2 - a soil line adjusted vegetation indexwas found to be the best predictor of LAI in the sensitivity analysis of Broge and Leblanc (2000) as it was least affected by the background reflectance.

In the present study, use of linear models in case of RDVI and SR and second order polynomial models in case of DVI, Log IR and IR were found to bemost appropriate. In case of NDVI, any of the three types of models i.e. linear, exponential and polynomial could be used with equal advantages whereas for MSAVI2 and MSI choice could be made either of the linear and exponential models and linear

**Table 1:** Formulae for computation of various spectral vegetation indices (SVIs) usingIRS LISS III band reflectance{Red (R) and near Infrared (NIR)}

| SVIs | Equation | Reference |
|---|---|---|
| DVI | NIR – R | Tucker (1979) |
| SR | NIR / R | Birth and McVey (1968) |
| NDVI | (NIR – R) / (NIR + R) | Rouse *et al.* (1973) |
| RDVI | (NDVI * DVI) | Roujean and Breon (1995) |
| MSI | (SWIR / NIR) | Rock *et al.* (1986) |
| MSAVI2 | $NIR + 0.5 - \sqrt{[(NIR + 0.5)^2 - 2(NIR - R)]}$ | Qi *et al.* (1994) |

**Table 2:** Prescribed spectral models (linear, exponential and polynomial regression equations) for wheat LAI estimation in Punjab, India

| Band reflectance/ spectral indices | Linear | Exponential | Polynomial |
|---|---|---|---|
| IR | Y = 0.04x+0.119 | $Y = 52.85e^{0.151x}$ | $Y = -0.00074x^2+0.2028x-8.564$ |
| Log IR | Y = 10.32x-16.44 | $Y = 1.5401e^{0.0099x}$ | $Y = -37.76x^2+163x-170.7$ |
| DVI | Y = 0.036x+1.545 | $Y = 2.119e^{0.0092x}$ | $Y = -0.00032x^2+0.085x-0.26$ |
| SR | Y = 0.75x+1.356 | $Y = 2.0062e^{0.192x}$ | $Y = -0.102x^2+1.518x-0.04$ |
| NDVI | Y = 6.208x+0.677 | $Y = 1.645e^{1.633x}$ | $Y = 9.745x^2-3.578x+3.031$ |
| RDVI | Y = 0.505x+0.951 | $Y = 1.802e^{0.1299x}$ | $Y = -0.007x^2+0.587x+0.709$ |
| MSI | Y = 2.961x+5.523 | $Y = 5.8688e^{-0.773x}$ | $Y = -8.966x^2+5.188x+3.842$ |
| MSAVI2 | Y = 6.753x-0.657 | $Y = 1.1443e^{1.793x}$ | $Y = 15.95x^2-13.86x+5.837$ |

**Table 3:** Error statisticsfor wheat LAI estimation using spectral based regression models (linear, exponential and polynomial)

| Band reflectance/ spectral indices | Bias (%) | | | RMSE(%) | | | $R^2$, n=30 | | |
|---|---|---|---|---|---|---|---|---|---|
| | Linear | Expo-nential | Polyn-omial | Linear | Expo-nential | Polyn-omial | Linear | Expo-nential | Polyn-omial |
| IR | -1.6 | -0.3 | 0.1 | 8.9 | 9.7 | 7.4 | 0.64 | 0.68 | 0.74 |
| Log IR | -0.3 | -0.4 | 0.0 | 8.2 | 8.9 | 7.3 | 0.68 | 0.60 | 0.74 |
| DVI | -0.3 | 0.0 | -0.1 | 6.8 | 7.8 | 6.1 | 0.75 | 0.72 | 0.79 |
| SR | 0.0 | -0.3 | 0.1 | 7.3 | 7.7 | 7.1 | 0.71 | 0.70 | 0.73 |
| NDVI | 0.0 | -0.3 | 0.0 | 7.5 | 7.2 | 7.2 | 0.70 | 0.72 | 0.72 |
| RDVI | 0.0 | -0.2 | -0.3 | 6.3 | 6.6 | 6.3 | 0.78 | 0.78 | 0.78 |
| MSI | 0.0 | -0.6 | 0.0 | 10.3 | 10.6 | 9.6 | 0.41 | 0.42 | 0.49 |
| MSAVI2 | 0.0 | -0.3 | 0.1 | 7.8 | 7.5 | 7.2 | 0.67 | 0.70 | 0.71 |

and second order polynomial models respectively.

## CONCLUSION

In this study, the potential of the visible to shortwave infrared reflectance data sourced from LISS IIIsensor of IRS satellite for estimating LAI of wheat crop was examined. The results showed a strong statistical dependence of the ground observed LAI withIR and Log IR bands' reflectances as well as with six spectral vegetation indices, viz. RDVI, DVI, NDVI, SR, MSAVI2 and MSI derived from LISS III bands. Such relationship was successfully modelled through linear and non-linear regression analyses. Use of linear and polynomial models (second order)rather than the exponential one is found to be more appropriatefor most of the spectral features tested here.However, keeping in view the accuracy of estimates, 24 models developed under the scope of this study were considered highly useful. RDVI based linear model is recommended for satellite based mapping of wheat-LAI and forcing such estimates as input into thecrop simulation modelsfor regional productivity estimation in Punjab, India.

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